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Research article

Reliability analysis and maintenance scheduling of solar photovoltaic systems using FMEA: A case study of Lango, Uganda

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ABSTRACT

This study examines the reliability and maintenance of solar photovoltaic (PV) systems in Lango, Uganda, using a descriptive survey of 280 respondents, site observations, Failure Modes and Effects Analysis (FMEA), and exponential reliability modelling. Aggregate reported-event counts were 460 for solar panels, 965 for batteries, 690 for inverters, and 310 for charge controllers. Using a nominal exposure of 102,200 component-days per class, estimated event rates were 0.004501, 0.009442, 0.006751 and 0.003033 day^{-1}, respectively, with corresponding 95% Poisson/chi-square confidence intervals of 0.004099–0.004932, 0.008856–0.010057, 0.006257–0.007275 and 0.002705–0.003390 day^{-1}. Under an independent exponential series model, calculated system reliability was 1.40% at 180 days and 0.01733% at 365 days. These estimates are conditional on nominal exposure and unverified classification of reported events as functional failures. An analytical cost and availability model compares corrective, age-based, and grouped maintenance policies. The constant-hazard model predicts no preventive-maintenance reliability gain; an optimal interval requires intervention costs, outage durations, and measured maintenance effects. The findings identify priorities for validating operational records and developing component-specific maintenance policies.

1. Introduction

Solar photovoltaic (PV) systems support electricity access in Uganda, particularly in rural and semi-urban settings [1]. Uganda's regulatory and policy challenges provide a broader context for energy-system planning [2]. Sustained PV operation depends on installation quality, component condition, maintenance capacity, and access to replacement parts [3–5]. Environmental conditions, including dust, shading, temperature, and moisture, can affect output and component condition [6–8]. These concerns motivate an assessment of maintenance needs in the Lango sub-region of northern Uganda. This study combines survey findings, site observations, Failure Modes and Effects Analysis (FMEA), and conditional exponential reliability calculations. Aggregate event counts and nominal exposure factors support reproducible rate calculations, but the absence of event-level histories limits interpretation. The analysis therefore distinguishes reported maintenance experience and expert priorities from confirmed functional-failure rates and validated maintenance benefits. The study provides a regional description of PV maintenance challenges and an analytical framework for examining maintenance decisions. FMEA identifies inspection priorities, while aggregate event summaries provide conditional rate and reliability estimates. A cost and availability formulation identifies the information needed to compare maintenance policies. The study does not establish causal effects of maintenance, a validated local failure process, or a

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numerical optimal schedule. Sections 2–6 present related work, methods, results and discussion, conclusions, and future work, respectively.

2. Related work

Reliability is the probability that a system or component performs its required function for a specified duration under defined conditions [3,9]. Maintainability concerns restoration of function, while availability accounts for the service time delivered over operating and restoration cycles [10–15]. These measures require consistent definitions of failure, exposure, and repair. Previous PV studies have examined time-varying failure rates [16], reliability and maintainability models [14], and probabilistic assessment of component availability [6]. Environmental conditions and installation quality can affect performance, while inadequate maintenance knowledge and limited access to repair services can delay restoration [4,5,8]. These findings motivate local data collection but do not establish the magnitude of failure rates or the effects of maintenance in Lango. Table 1 summarises the reviewed studies and the regional questions that remain.

The literature identifies a need to connect operational records with technical, financial and service constraints. For Lango, the main unresolved questions concern failure classification, operating exposure, restoration delays and the effects of specific maintenance actions. The present survey and aggregate calculations provide a basis for formulating these questions; longitudinal observations are needed to test maintenance policies. Recent diagnostic studies provide methods for investigating the physical condition of PV modules. Verma et al. [23] examined mechanical stress in mono-PERC and polycrystalline modules using electroluminescence (EL) imaging, electrical testing, and statistical analysis. Verma et al. [24] applied YOLOv11 to infrared (IR) images for module defect detection. These approaches motivate objective inspection of suspected module defects, but detection of an image anomaly alone does not establish a functional failure, a failure date, or an exposure-based failure rate. Their diagnostic findings cannot validate the aggregate Lango event counts. Policy and energy-management studies address a complementary scale of analysis. Hussain et al. [25] discuss solar policy instruments, financing and barriers to sustainable deployment. Lal et al. [26] examine AI applications for renewable-energy integration and carbon reduction in buildings. These studies provide context for service access, monitoring, and energy planning. Their policy and building-system findings do not establish causal socio-economic effects, local intervention costs, or hardware reliability improvements in the present survey.

Connected monitoring introduces communication-security requirements. Chauhan et al. [27] examine lightweight end-to-end encryption for solar PV IoT devices. Their work connects device resource requirements and communication overhead to the feasibility and cost of monitoring. This perspective informs the prospective monitoring assessment in Section 6.1; connected monitoring was not deployed in the present study. Performance optimization must also be distinguished from failure prevention. Choudhary et al. [28] investigated seasonal PV tilt optimization in Rajasthan, India. Their location-specific energy-yield analysis does not supply an optimum tilt or maintenance interval for Lango. Verma and Yadav [29] review PV degradation mechanisms and diagnostic methods, including visual, thermal, and EL assessment. Together, these studies support separate measurement of environmental performance losses, physical degradation, and functional failures. Local irradiance, configuration, operating histories, and condition measurements remain necessary before transferring diagnostic or optimization results to the systems considered here.

Table 1
Summary of the related studies with different approaches.

Author(s)	Research Focus	Research Gap
Wassie & Adaramola, 2021 [17]	Socio-economic and environmental impacts of rural electrification using solar PV systems in southern Ethiopia.	Evidence from southern Ethiopia provides regional context, but does not establish component failure rates, maintenance effects, or product-quality impacts in Lango. These require local technical and service records.
Alinaitwe, G., 2023 [18]	Determinants of solar PV adoption in Uganda.	Adoption evidence provides national context; component failures and restoration in Lango require separate technical records.
Mustafa, et al., 2020 [19]	Environmental effects on solar PV performance.	Local measurements are needed to distinguish environmental output losses from functional component failures.
Tillmans & Schweizer-Ries, 2011 [5]	Knowledge communication about solar home systems from the perspective of Ugandan consumers.	Regional training and educational needs for sustained PV operation in Lango require further study.
Aboagye, et al., 2022 [20]	Effects of design, installation, operation, and maintenance issues on installed PV performance and degradation.	Installation quality, maintenance, and degradation require assessment against dated local operating and service histories.
Osmani, et al., 2020 [21]	Review of maintenance strategies for PV systems.	Local policy comparison depends on verified event histories, intervention costs, downtime, and service requirements.
Pimpalkar, et al., 2023 [22]	Review of failure modes and effects analysis for solar PV systems.	Expert FMEA prioritisation needs separate empirical validation against classified events and operating exposure.

3. Materials and methods

3.1. Conceptual framework

Reliability-centred maintenance (RCM) provides the conceptual framework for identifying required functions, potential failure modes, consequences and candidate maintenance actions [30,31]. Environmental conditions, installation quality and maintenance practice are considered possible influences on PV performance. These factors organise the survey and maintenance discussion; they are not fitted predictors in a statistical model. The study does not estimate their causal effects or demonstrate an optimized RCM policy.

The socio-economic factors shown in Fig. 1, including funding, technician access, policy support, awareness, and training, are potential service constraints. Survey ratings describe respondents' perceptions of these factors. Moderating effects and associations with observed failures or restoration times were not estimated.

3.2. Research design

The mixed-methods design comprised distinct descriptive survey, expert FMEA and aggregate-event analyses (Fig. 2). Surveys, interviews and site observations described maintenance practices, reported problems and perceived service constraints. Expert scores supported FMEA prioritisation. The quantitative reliability analysis used aggregate component event counts and nominal exposure factors, as specified in Section 3.6, without numerical input from survey percentages or manufacturer failure-rate and MTBF specifications. Rates were calculated from counts and exposure; MTBF and reliability were then derived. These information sources informed different questions and were not linked at event or respondent level. Candidate maintenance actions and an analytical cost and availability comparison were formulated; implementation, expenditure savings, and changes in availability were not

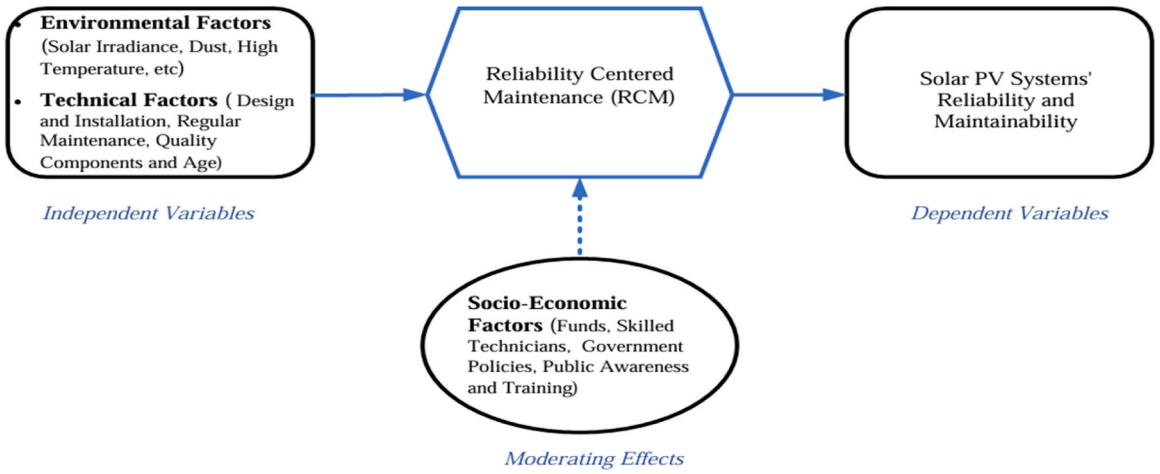

Fig. 1. Conceptual factors considered in the maintenance assessment. Arrows indicate proposed relationships, not estimated causal effects or statistically tested associations.

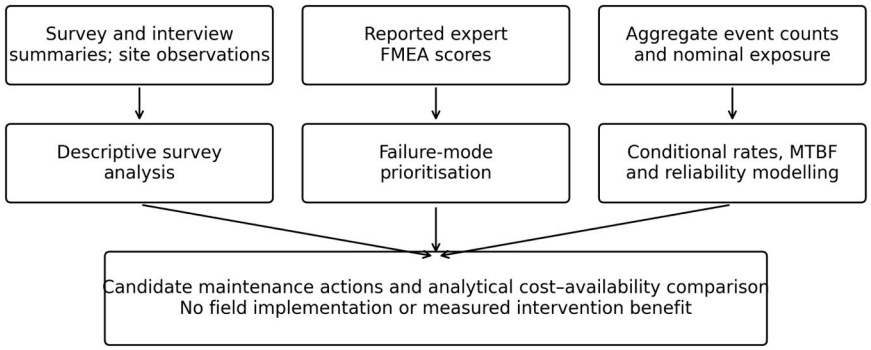

Fig. 2. Study workflow showing reported data inputs, completed analyses and analytical outputs. Maintenance implementation and its effects were not evaluated.

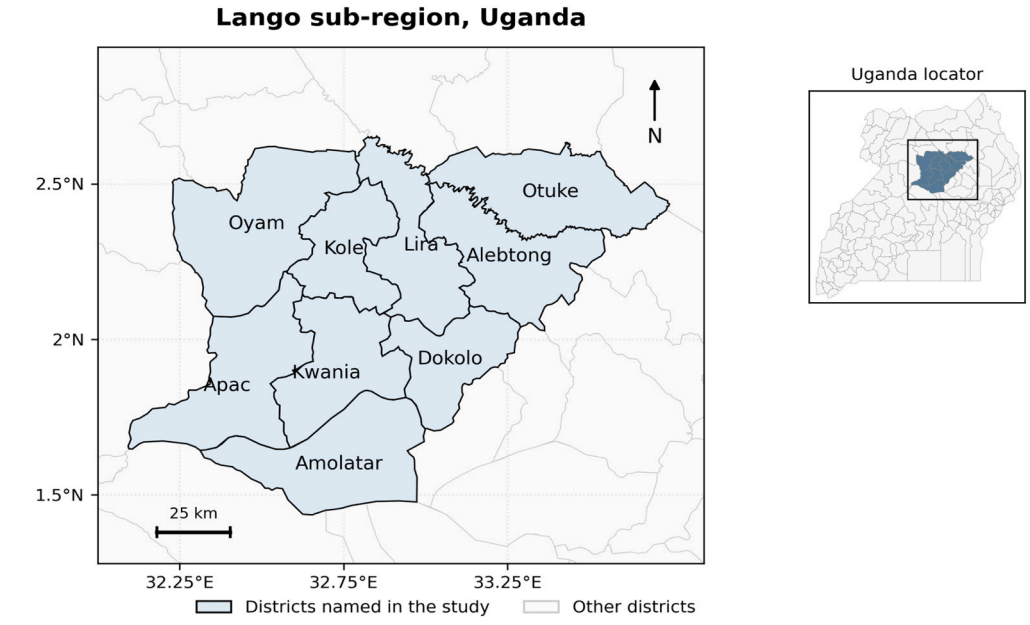

Fig. 3. Administrative setting of the study in the Lango sub-region, Uganda. Shading identifies the nine districts named in the study design, rather than verified sampling coverage. Sampled-site markers are not shown because site locations are undocumented. Authors' cartography uses Uganda Bureau of Statistics district boundaries, with WHO support, dated 24 August 2020 and hosted by UNITAR–UNOSAT [32].

measured.

3.3. Study area

The study area was the Lango sub-region of northern Uganda, comprising the nine districts identified in the study design: Alebtong, Amolatar, Apac, Dokolo, Kole, Kwania, Lira, Otuke and Oyam. The approximate coordinate 02°18′N, 33°00′E provides a regional reference point rather than the geographic extent of the study or a sampled-system location. Fig. 3 shows the administrative setting using the Uganda Bureau of Statistics district boundary layer dated 24 August 2020, produced with WHO support and hosted by UNITAR–UNOSAT [32]. This boundary date identifies the cartographic source and does not specify the survey period. The map locates the named districts; the available records do not identify sampled-system coordinates, villages or parishes, or the number of usable responses from each district. Accordingly, the spatial distribution of the 280 analysed systems cannot be resolved from these summaries.

3.4. Sampling design and sample-size assumptions

The sampling design specified stratification by user category (households, institutions and businesses) and district, with random selection within strata. This design was intended to include different user groups and geographic areas. However, stratum population sizes, allocation totals, selection probabilities, and district-specific achieved samples were not retained in the available summaries. Proportional allocation and the geographic representativeness of the realised sample therefore cannot be verified. The population-size calculation used a household-based planning scenario for PV systems rated above 100 W. Eq. (1) gives the finite-population expression used to examine the stated planning inputs.

$$n = \frac{NZ^2p(1-p)}{(N-1)e^2 + Z^2p(1-p)} \tag{1}$$

In Eq. (1), N denotes the assumed eligible population, $Z = 1.96$ specifies a nominal 95% confidence level, $e = 0.05$ is the planning margin of error, and $p = 0.80$ is the assumed outcome proportion. The household planning base was 514,500, with assumed solar adoption of 20% and an assumed above-100-W share of 10% among solar households. The resulting assumed eligible household population was $N = 10,290$. These shares are planning assumptions, not measured Lango-level estimates or IEA data. The source table, reference period, and geographic coverage of the household base remain unverified. The calculation retained $p = 0.80$ as a planning assumption. It is not an observed proportion for an outcome among eligible PV users. In particular, the complement of assumed solar adoption in the general household population does not estimate an outcome proportion within a sample restricted to PV owners. The household-derived N also excludes a separate enumeration of eligible institutions and businesses. Thus, the calculation is a conditional household planning scenario rather than a verified sample-size determination for all three user categories. Under the stated assumptions, Eq. (1) gives an approximate sample-size requirement of 240 participants. Rounding upward to the next whole participant gives a conditional minimum of 241.

The final analytical sample comprised 280 complete and usable responses, exceeding the conditional minimum of 241 by 39 participants (Table 2). Thus, the achieved sample was larger than the calculated requirement. The available summaries do not independently establish the total number of eligible users approached or the number of incomplete and non-returned questionnaires; a response rate cannot therefore be determined. Survey percentages in Figs. 4–9 use the 280 usable responses as the denominator. Eq. (1) assumes simple random sampling from a defined finite population. Exceeding its conditional minimum does not establish the achieved precision or representativeness of the stratified survey, which also depends on frame coverage, stratum allocation, selection probabilities, and non-response. District-specific counts and individual site locations remain undocumented.

Table 2
Conditional sample-size requirement and final analytical sample.

Sampling quantity	Value
Conditional minimum sample size, rounded upward	241
Complete and usable responses analysed	280
Responses above the conditional minimum	39

3.5. Participant inclusion and missing-data management

A complete case analysis was applied, and the survey records were screened for missing entries, duplicate responses, internal inconsistencies, and compliance with the eligibility criterion of operating a solar PV system rated above 100 W. Records that did not meet these requirements or contained incomplete information were excluded from the final analysis. Following data screening, 280 complete and usable records were retained. No statistical imputation was performed. Accordingly, the denominator for all survey-based descriptive analyses presented in Figs. 4–9 was $n = 280$. Percentages were calculated by dividing the frequency in each response category by 280 and multiplying by 100.

3.5.1. Ethical approval, consent, and data protection

Ethical approval for this study was obtained from the Kampala International University Research Ethics Committee (REC), reference KIU-8282, before data collection commenced. All participants received information explaining the purpose of the study, the procedures involved, the voluntary nature of participation, and their right to decline or withdraw without penalty. Written or verbal informed consent was obtained from each participant before the administration of surveys or interviews and before site inspections involving participant interaction. To protect confidentiality, participants' names and other direct personal identifiers were not included in the analytical dataset. Each participant's record was assigned a unique identification code, and the survey and interview data were analysed and reported in aggregate form. Electronic data were stored in password-protected files accessible only to the research team, while any physical records were kept securely. The collected data were used solely for this study.

3.5.2. Failure definition and unit of analysis

In the reliability model, the unit of analysis is one installed functional component block within one PV system: the PV generating assembly, battery storage assembly, inverter, or charge controller. A generating assembly may contain several modules, and a storage assembly may contain several batteries or cells. These physical subunits are distinct from the functional blocks represented in the series model. The survey unit is the respondent-associated PV system; a survey response is neither an individual component nor a failure event. The aggregate records do not establish whether all reported events were counted at module, battery, bank, or assembly level. A qualifying component functional failure is loss of the ability to perform the required electrical function safely under adequate energy input, rated loading and the specified operating conditions, because of a component fault or damage. The relevant functions are DC generation for the PV assembly, storage and delivery of usable DC energy for the battery assembly, DC-to-AC conversion for the inverter, and charge regulation and protection for the controller. Complete loss of output and partial loss that breaches a documented service or safety requirement both qualify. No numerical failure threshold is imposed retrospectively because the source summaries do not provide system-specific voltage, power, capacity or protection limits. Low irradiance, normal battery depletion, and overload beyond rated conditions alone do not establish component failure.

Soiling is classified separately as a reversible environmental or

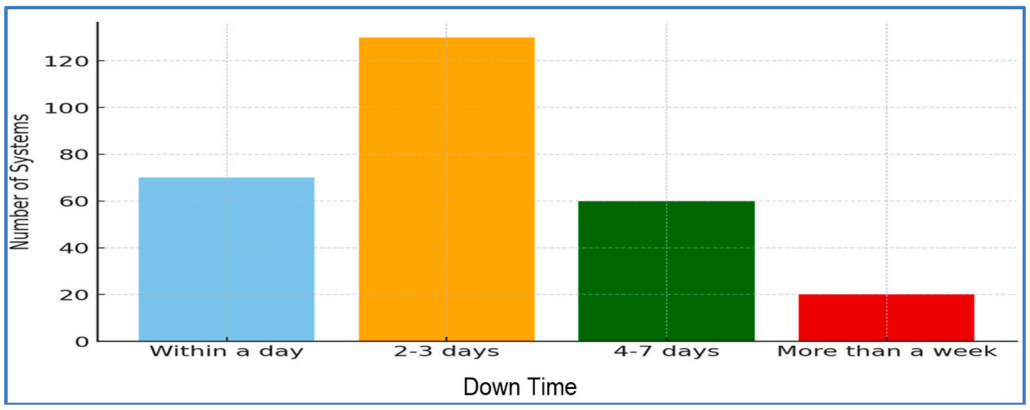

Fig. 4. Respondent-reported restoration-duration categories in Lango, Uganda ($n = 280$). These categories do not measure current operating status or time-based availability.

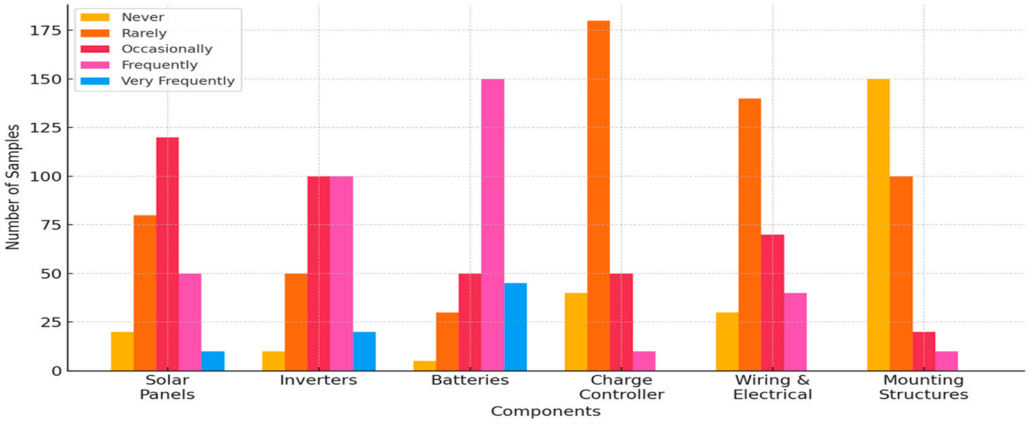

Fig. 5. Respondent-reported component problem-frequency categories in Lango, Uganda ($n = 280$ respondents per component). Source: survey responses; percentages are response proportions, not verified failure rates.

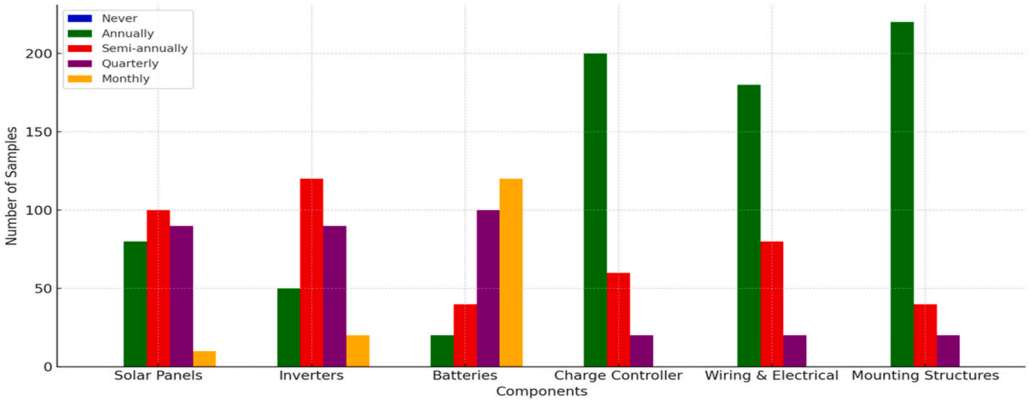

Fig. 6. Respondent-reported component maintenance frequency in Lango, Uganda ($n = 280$ respondents per component). Source: survey responses; servicing frequency does not measure functional-failure frequency.

performance condition when dust or dirt reduces output without component damage. A service interruption attributable solely to soiling is an environmental service event, rather than an intrinsic component failure. A minor fault or warning is a detectable abnormality while the required function and safety requirements remain satisfied; if it causes loss of required function, its classification changes to functional failure irrespective of repair cost or duration. A maintenance event is an inspection, cleaning, adjustment, scheduled service, or preventive replacement. Such an action does not by itself constitute a failure. Corrective work is linked to the originating failure where one exists, rather than counted as a second event. The event-counting unit is a distinct loss-of-function episode for a uniquely identified component block. Repeated reports, technician visits, fault codes, and repair actions associated with the same uninterrupted episode represent one failure. A further recurrent failure requires documented restoration followed by a new loss of function. Component events and system outages are separate measures: simultaneous failures of two blocks may produce two component events but only one system outage. In a recurrent-event

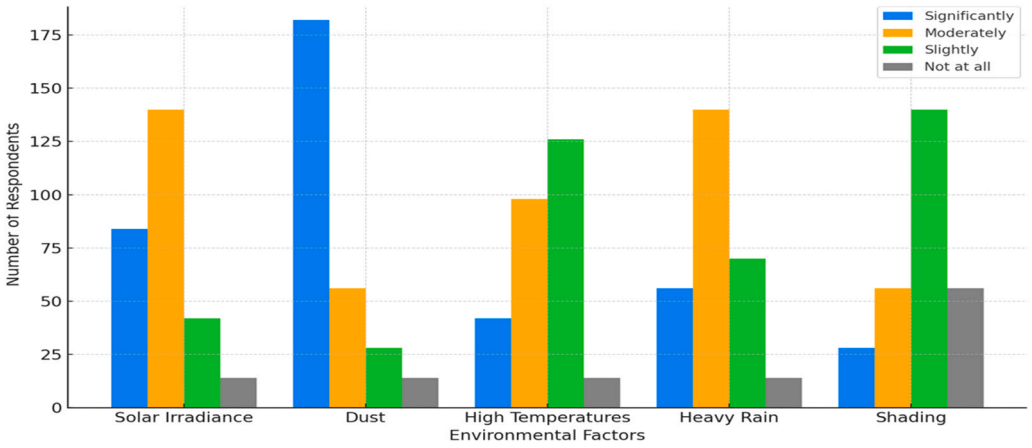

Fig. 7. Respondent-perceived environmental influences on PV performance in Lango, Uganda ($n = 280$ per factor). Source: survey ratings, not measured failure events or energy losses.

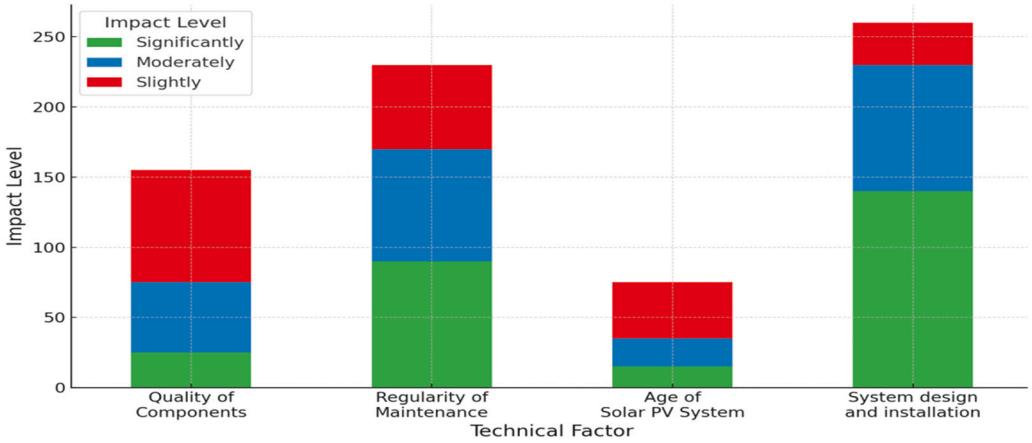

Fig. 8. Respondent-perceived technical influences on PV performance in Lango, Uganda ($n = 280$ per factor). Source: survey ratings; percentages do not estimate effects on λ.

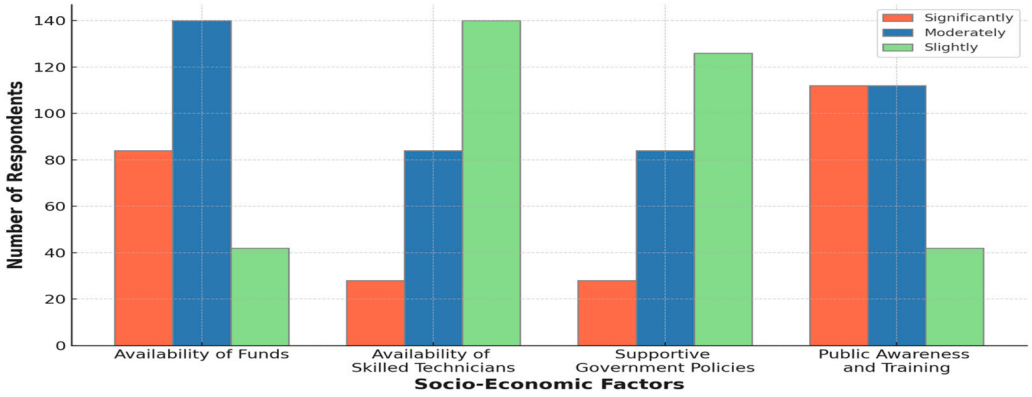

Fig. 9. Respondent-perceived socio-economic influences on PV performance in Lango, Uganda ($n = 280$ per factor). Source: survey ratings; percentages do not establish associations with failure rates.

analysis, exposure accumulates while the identified block is at risk, excluding documented downtime and including eligible censored intervals.

This classification defines the functional-failure endpoint for interpretation of the model. The available aggregate counts do not identify the function lost, event cause, maintenance action, or restoration history and therefore cannot be retrospectively separated into qualifying failures, soiling, minor faults, and maintenance events. No category-specific counts have been imputed. Table 5 retains the original aggregate reported-event counts; its λ estimates represent component failure rates only if those events satisfy the functional-failure definition and correspond to the stated component units. Otherwise, they describe a broader reported-event frequency. The same qualification applies to the derived MTBF and reliability projections.

3.5.3. FMEA scoring procedure

Five experts in solar PV installation, operation, maintenance, and fault diagnosis conducted the FMEA. Each expert scored severity (S), occurrence (O), and detection (D) on a scale of 1–10. A score of 1 represented negligible severity, rare occurrence, or high detectability; a score of 10 represented catastrophic severity, frequent occurrence or very low detectability [33,34]. Individual scores were averaged and rounded to the nearest whole number. Differences were discussed with reference to field observations and maintenance summaries. Eq. (2) defines the Risk Priority Number (RPN). The assessment includes performance conditions, such as soiling, as well as functional failure modes. Expert occurrence scores are not observed event counts or failure-rate estimates; FMEA inclusion does not establish eligibility for N_i under Section 3.5.2.

$$\mathrm{RPN} = S \times O \times D \tag{2}$$

In Eq. (2), S denotes severity, O denotes occurrence, and D denotes detection difficulty. Higher RPN values indicate higher maintenance priority under the adopted scoring scheme. Table 3 presents the final aggregated expert scores for each assessed mode or condition. RPNs are dimensionless prioritisation scores derived from the adopted ordinal ratings. They are reported as scores rather than percentages of a total and do not estimate failure probability, population prevalence or a component's contribution to downtime.

3.5.4. Data sources and analytical roles

Respondent survey summaries describe recalled component problems and maintenance practices (Figs. 5 and 6) and perceived environmental, technical and socio-economic influences (Figs. 7–9). Their percentages use respondents, not failures or operating time, as the denominator. Fig. 4 likewise describes reported restoration-duration categories. These summaries were analysed descriptively and were not converted into event counts, failure probabilities, λ estimates, or MTBF values. The rate analysis used a separate numerical input source: aggregate component event counts and nominal exposure factors transcribed from source summaries (Table 5). Eq. (3) estimates λ from these counts and exposures; MTBF and modelled reliability are derived outputs (Tables 4 and 6). These summaries are not an independently auditable event register, and their classification and exposure limitations remain as specified in Section 3.6. Survey responses were not linked to individual dated failures, so respondent percentages cannot corroborate the rate estimates or establish associations between perceived factors and failure risk.

Expert FMEA ratings form a third analytical input (Table 3). Their severity, occurrence, and detection scores support prioritisation of candidate actions; the occurrence score is not an empirical failure count or rate. FMEA scores, survey percentages and aggregate-event estimates are reported separately and are not treated as mutual validation.

3.6. Reliability analysis and model assumptions

The rate-analysis inputs were aggregate reported-event counts of 460 for panels, 965 for batteries, 690 for inverters, and 310 for controllers, and a common nominal exposure of 102,200 component-days per class (280 nominal system-component units over 365 days). Counts and exposure factors were transcribed directly from explicit aggregate expressions in the source summaries. Rates were calculated from these inputs using Eq. (3) [35], with MTBF derived subsequently. Rounded MTBF values and manufacturer specifications were not rate inputs. The summaries establish the arithmetic inputs but do not independently verify event provenance, classification, or exposure. Events remain unclassified aggregate reports under Section 3.5.2.

Table 4
Conditional MTBF derived from aggregate reported-event counts and nominal exposure.

Component	Rate estimate $\widehat{\lambda_i}$ (day^{-1})	Conditional MTBF (days)
Solar panels	0.004501	222.17
Batteries	0.009442	105.91
Inverters	0.006751	148.12
Charge controllers	0.003033	329.68

$$\widehat{\lambda_i} = \frac{N_i}{T_i} \tag{3}$$

Here, N_i denotes the aggregate reported-event count for component class i, and T_i denotes its nominal exposure in component-days. For $\widehat{\lambda_i}$ to estimate a functional component-failure rate, each counted event must meet Section 3.5.2 and refer to the same component unit as the exposure denominator. The factor 280 is the system multiplier in the aggregate calculation and does not independently verify the component inventory. Counts exceed 280 in every class, so a recurrent-event or multiple-unit basis would be needed rather than first failures among 280 units. Neither basis can be confirmed from the summaries. MTBF was derived after rate estimation using Eq. (4) and provides no independent validation of event eligibility:

$$\mathrm{MTBF}_i = \frac{1}{\widehat{\lambda_i}} = \frac{T_i}{N_i} \tag{4}$$

The aggregate calculations provide component-level counts and a nominal 365-day duration, but no anonymised event register. System and component identifiers, entry dates, failure and restoration dates, replacement histories, exit or last-contact dates, censoring indicators and reasons are not available. Accordingly, the nominal exposure of 102,200 component-days cannot be verified as net observed operating time. The 365-day duration is an exposure assumption rather than a documented calendar observation window.

For recurrent-event rate estimation, total operating exposure is the sum of observed at-risk intervals, including terminal censored intervals and excluding downtime. Each restoration or replacement requires a corresponding event record to distinguish recurrent failures from duplicate reports and to define the component at risk. Cleaning, servicing, and soiling do not necessarily constitute functional failures. These distinctions could not be assessed from the aggregate counts and nominal exposure factors. A separate inverter summary reports five failures over 10,000 operating hours, corresponding to 0.012 day^{-1} under a 24-hour-day conversion. This conflicts with the aggregate estimate of 0.006751 day^{-1}. Its observation basis is unspecified; it was not pooled with the aggregate counts used in Table 5.

For failures following a homogeneous Poisson process over fixed, known operating exposure, $N_i \sim \mathrm{Poisson}(\lambda_i T_i)$ and $\widehat{\lambda_i} = \frac{N_i}{T_i}$. For $N_i > 0$,

Table 3
FMEA prioritisation of component failure modes and performance conditions.

Components	Failure mode or performance condition	Severity (S)	Occurrence (O)	Detection (D)	RPN (score)
Solar panels	Soiling, dust, or dirt (environmental performance condition)	6	8	4	192
Batteries	Overheating	9	4	5	180
Inverters	DC-AC conversion failures	9	4	5	180
Charge controllers	Component failure	8	4	4	128

Table 5
Aggregate reported events and conditional rate estimates by component class.

Component	EventsN_i	Nominal systems[1]	Nominal days[a]	Exposure T_i[1](component-days)	$\hat{\lambda}_i$(day^{-1})	Conditional 95% CI (day^{-1})
Solar panels	460	280	365	102,200	0.004501	0.004099–0.004932
Batteries	965	280	365	102,200	0.009442	0.008856–0.010057
Inverters	690	280	365	102,200	0.006751	0.006257–0.007275
Charge controllers	310	280	365	102,200	0.003033	0.002705–0.003390

[a] The source summaries specify 102,200 nominal component-days per class, based on 280 system-component units and 365 days, and the aggregate event counts reported here. Rates are calculated from these counts and exposure factors, not by inverting the displayed MTBF values. The factor 280 does not establish component multiplicity or a verified longitudinal system roster. Actual observation dates, failure and restoration histories, and censoring/downtime adjustments are not reported. Confidence intervals assume valid fixed exposure and homogeneous Poisson failures and do not include uncertainty in these assumptions. Calculations use unrounded N_i/T_i ratios. N_i retains the aggregate reported events; separate counts of functional failures, soiling, minor faults and maintenance actions are unavailable. The rates are conditional estimates of functional-failure intensity only if all counted events meet Section 3.5.2.

Table 6
Conditional exponential component reliability based on aggregate counts and nominal exposure.

Component	MTBF (days)	Reliability at 180 days	Reliability at 365 days
Solar panels	222.17	0.445 (44.5%)	0.193 (19.3%)
Batteries	105.91	0.183 (18.3%)	0.032 (3.2%)
Inverters	148.12	0.297 (29.7%)	0.085 (8.5%)
Charge controllers	329.68	0.579 (57.9%)	0.331 (33.1%)

the central exact Poisson 95% confidence interval is obtained from chi-square quantiles as [35]:

$$\lambda_{i,L} = \frac{\chi^2(0.025; 2N_i)}{2T_i}$$
$$\lambda_{i,U} = \frac{\chi^2(0.975; 2N_i + 2)}{2T_i} \quad (5)$$

Here $\chi^2(p;\nu)$ is the lower-tail p-quantile of a chi-square distribution with ν degrees of freedom. For $N_i = 0$ and $T_i > 0$, the central two-sided 95% interval is $\left[0, -\frac{\ln(0.025)}{T_i}\right]$, while the one-sided 95% upper bound is $-\frac{\ln(0.05)}{T_i}$. Table 5 gives central two-sided intervals calculated from the extracted aggregate counts and nominal exposure. These intervals are conditional on a homogeneous Poisson process and fixed, valid exposure; they do not account for uncertainty in the exposure denominator, misclassified events, clustering, or informative censoring. For positive rate limits, the corresponding MTBF confidence interval is $\left[\frac{1}{\lambda_{i,U}}, \frac{1}{\lambda_{i,L}}\right]$, and the component reliability interval at a fixed time t is $\left[\exp(-\lambda_{i,U}t), \exp(-\lambda_{i,L}t)\right]$. A zero lower rate limit gives an unbounded upper MTBF limit. Individual component intervals do not provide simultaneous confidence bounds for series-system reliability. The uniform ±10% rescaling of all component rates is a simple deterministic parameter perturbation illustrating the resulting changes in calculated reliability.

The reliability of each component was estimated using the exponential reliability model:

$$R_i(t) = e^{-\lambda_i t} \quad (6)$$

Here $R_i(t)$ is the probability that component i operates without a qualifying failure up to operating time t, and λ_i is its assumed constant failure rate.

The exponential model in Eq. (6) assumes a constant hazard and memoryless component lifetimes. It contains no maintenance-effect term: λ is unchanged by inspection, servicing or planned replacement in the present analysis. For a surviving component, the conditional probability of surviving an additional operating duration u is $\exp(-\lambda u)$, irrespective of its current operating age. Perfect replacement with an identically distributed exponential component therefore does not lower the subsequent hazard. At equal accumulated operating exposure, this model predicts no PM-induced improvement in failure-free survival. Planned service interruptions are accounted for in availability and downtime, not treated as a reduction in intrinsic failure risk. For recurrent failures, the corresponding homogeneous Poisson process assumes independent increments and a constant event rate on the operating-time scale. Aggregate inputs did not permit estimation of age-dependent hazards or intervention effectiveness; comparison with such models requires longitudinal event and maintenance histories. Component failures were modelled as statistically independent because the aggregate summaries contained no event timestamps or common-cause information with which to estimate dependence. Independence is a modelling assumption, not a finding about the installations. Shared environmental and electrical stresses, including temperature, moisture, voltage fluctuations, and installation defects, can produce dependent failures. The system reliability values are conditional projections for the independent configuration; dependence remains unquantified.

The solar PV system was represented as a non-redundant series system comprising the solar panel, battery, inverter, and charge controller. This representation was selected because each of these components is required for the intended operation of the systems considered in the analysis. Under the series-system assumption, failure of any essential component interrupts the intended power-supply function. Overall system reliability was therefore calculated as:

$$R_s(t) = \prod_{i=1}^{n} R_i(t) \quad (7)$$

For exponentially distributed and independent component failures, this becomes:

$$R_s(t) = e^{-t\sum_{i=1}^{n}\lambda_i} \quad (8)$$

The series model does not represent installations containing backup batteries, parallel inverters, bypass arrangements, spare charge controllers, or other forms of functional redundancy. For systems with such configurations, the present model may underestimate actual system reliability. Eqs. (7 and 8) describe survival without a qualifying interruption, not the probability of being operational after repair. Restoration returns a repairable system to service but does not remove a failure already experienced during the mission. Failure-free reliability, restoration duration, and service availability are therefore separate endpoints. A simple parameter perturbation uniformly multiplied all component rates by 0.9 and 1.1, with all other model assumptions held fixed. At 180 days, calculated series-system reliability ranged from 0.91% with rates increased by 10–2.14% with rates reduced by 10%, compared with a baseline of 1.40%. At 365 days, the corresponding range was 0.00729–0.04119%, compared with a baseline of 0.01733%.

Uniform rescaling necessarily preserves the component ranking because the relative rates remain unchanged. The reported ranges illustrate the effect of these two parameter perturbations; they are neither statistical confidence intervals nor evidence of model robustness. This exercise does not assess independent component-rate variation, uncertainty in event classification or exposure, or alternative model structures.

3.6.1. Scope of the restoration-time assessment

Restoration experience was described using the respondent-reported downtime categories in Fig. 4. These grouped reports do not distinguish active repair from technician response, spare-parts waiting, administrative delays or other periods without service. Component-specific mean time to repair (MTTR), repair rates, repair-time distributions, maintainability functions and empirical availability were therefore not estimated. The modal restoration category cannot be treated as a mean active repair duration. The available summaries also do not provide complete operating and outage histories over a common observation window or event-level downtime costs. The quantitative analysis is therefore restricted to the conditional event-rate and reliability calculations and descriptive restoration categories. Section 3.8 presents a separate, uncalibrated cost and availability model for analytical policy comparison. Its symbolic results do not constitute measured MTTR, availability or downtime costs for the sampled systems.

3.7. Formulation of candidate maintenance actions

The survey and FMEA informed the formulation of candidate preventive maintenance (PM) and corrective maintenance (CM) actions. These proposed actions were not implemented or evaluated as study interventions. The reliability analysis does not demonstrate that they reduce failure risk, and Section 3.8 provides only an analytical cost and availability comparison. Predictive maintenance (PdM), including IoT monitoring and remaining useful life prediction, was neither implemented nor experimentally validated and is discussed solely as future work in Section 6.1. The condition-triggered policy in Section 3.8 is an uncalibrated comparator, not an implemented PdM strategy.

3.7.1. Interpretation of survival quantiles

For a specified survival probability R_{target} and positive constant hazard λ, Eq. (9) gives the corresponding operating-time quantile from the component reliability model in Eq. (6). It is a survival-probability calculation, not a maintenance optimization:

$$T_{\text{i}} = -\frac{\ln\left(R_{\text{target,i}}\right)}{\lambda_{\text{i}}} \tag{9}$$

A component survival target specifies an acceptable probability of failure over a defined mission, taking account of load criticality, safety and the service agreement. The available data establish neither an acceptable survival threshold nor a preventive replacement age. Battery survival is distinct from state of charge, depth of discharge and retained capacity. Availability describes delivered service over operating and restoration periods, whereas mission reliability describes uninterrupted operation. Eq. (9) gives a survival quantile under the assumed hazard; it does not identify an effective maintenance action or demonstrate a reliability gain. Consequently, no numerical survival target or component-specific PM interval is adopted.

3.7.2. Corrective maintenance comparator

Corrective maintenance is defined here as restoration after a confirmed functional failure and is included as an analytical comparator, not a study-implemented intervention. Its acceptability depends on service criticality, failure consequences, restoration delays, and safety requirements. No component is assigned to run-to-failure solely because its aggregate reported-event rate is low, and no cost advantage is inferred without expenditure and outage data. Mandatory safety inspections and manufacturer-required servicing remain constraints on every policy.

3.8. Maintenance policy cost and availability model

Maintenance decisions are formulated as constrained long-run cost minimization using renewal-reward principles [36]. Cost categories follow the distinction between planned maintenance, corrective work, logistics, and lost service used in PV and storage O&M planning [37]. The formulation below is an analytical model; the available aggregate data do not provide a calibrated numerical optimum.

$$\begin{aligned} J(\pi) = \lim_{H\to\infty}\frac{1}{H}\mathrm{E}[&C_{\text{PM},\pi}(H) + C_{\text{CM},\pi}(H) + C_{\text{travel},\pi}(H) \\ &+ C_{\text{monitor},\pi}(H) + vD_{\pi}(H) + L_{\text{partial},\pi}(H)] \end{aligned} \tag{10}$$

Here H is calendar time in days; π is a feasible maintenance policy; C_{PM} and C_{CM} are cumulative parts and labour expenditures for planned and corrective work; C_{travel} is mobilization and travel expenditure per actual site visit; and C_{monitor} includes equipment, communications, and monitoring labour. Costs are expressed consistently in Ugandan shillings (UGX), so J has units of UGX per calendar day. D is the total duration of unavailable required service and v is its value in UGX per service-day. L_{partial} values partial service or energy shortfall while the system is available and excludes losses already charged through vD. Shared visits incur one trip charge; overlapping outages are counted by their union, not by adding component outage durations.

$$\begin{aligned} A(\pi) &= 1 - \lim_{H\to\infty}\frac{\mathrm{E}[D_{\pi}(H)]}{H} \\ \pi^{*} &\in \operatorname*{argmin}_{\pi} J(\pi), \text{subject to} A(\pi) \geq A_{\min} \end{aligned} \tag{11}$$

and safety and service constraints.

Eq. (11) assumes continuous required service. For scheduled loads or resource-dependent generation, availability is evaluated only during explicitly defined required service windows: the denominator is total required service time and the numerator of unavailability is its intersection with outages. Expected sunlight variation or insufficient irradiance is not automatically a component failure. $A_{\min}$ represents the availability requirement specified by critical-load needs and the owner's service agreement. A separate mission constraint, $\Pr(\text{loss of required function before h}) \leq \varepsilon$, may be imposed when a specified uninterrupted mission is required; neither h nor ε is inferred from a survival-quantile calculation.

For an analytical single-component comparison, consider replacement at operating age τ or upon earlier failure. Both PM and CM restore the component to an as-new condition; successive lifetimes are independent and identically distributed. Let S(t) be the lifetime survival function, $p = S(\tau), f = 1 - p$, and $u(\tau)$ the mean operating duration per renewal. Let d_{P} and d_{C} be finite mean planned and corrective service downtime per renewal, including relevant logistical delays; $c_{\text{P}} = C_{\text{P}} + K_{\text{P}}$ and $c_{\text{C}} = C_{\text{C}} + K_{\text{C}}$ are intervention parts and labour costs plus the associated trip costs. These constants are assumed independent of cycle length. For continuous service demand:

$$u(\tau) = \int_{0}^{\tau} S(t)dt; d(\tau) = pd_{\text{P}} + fd_{\text{C}} \tag{12}$$

$$G(\tau) = \frac{pc_{\text{P}} + fc_{\text{C}} + vd(\tau)}{u(\tau) + d(\tau)}; A(\tau) = \frac{u(\tau)}{u(\tau) + d(\tau)} \tag{13}$$

Here G is the long-run cost per calendar-day. The corrective-only policy is the limit $\tau\to\infty$, provided the mean lifetime is finite. For finite τ, costs and downtime accrue at the first of failure and the planned replacement age. Eqs. (12 and 13) describe restorative replacement or a demonstrably equivalent overhaul, not automatically inspection, cleaning, minor repair, or sensor installation. Such actions need a

measured effect on failure risk, repair duration, or energy yield. For age-dependent hazards, a fitted lifetime model, such as a justified Weibull model, can be evaluated in (12–13); fitting it requires individual operating-age and censoring records absent here. In the exponential baseline used here, the as-new assumption resets operating age without changing λ. Thus, the replacement-policy model accounts for renewal costs and downtime but provides no hazard-reduction benefit from PM. Inspection or servicing is not assumed to produce an as-new component.

For exponential lifetimes, define $z = \frac{1}{\exp(\lambda\tau)-1}$, $B = \frac{1}{\lambda} + d_C$, $Q_C = c_C + v d_C$ and $Q_P = c_P + v d_P$. The policy cost and availability are:

$$G(\tau) = \frac{Q_C + zQ_P}{B + zd_P}; A(\tau) = \frac{1}{1 + \lambda d_C + \lambda d_P z} \tag{14}$$

$$G_{CM} = \frac{Q_C}{B}; A_{CM} = \frac{1}{1 + \lambda d_C}$$
$$\frac{\partial G}{\partial z} = \frac{Q_P B - d_P Q_C}{(B + zd_P)^2} \tag{15}$$

The derivative has a constant sign for fixed non-negative costs and downtimes. Consequently, this exponential replacement model has no uniquely cost-minimizing interior age: if $Q_P B > d_P Q_C$, the corrective-only boundary minimizes G within the unconstrained policy family; equality makes G independent of age; if $Q_P B < d_P Q_C$, G favours the shortest feasible age, with feasibility constrained by availability and mandatory requirements. The last case can reflect less operating time rather than failure prevention and does not establish a beneficial arbitrary calendar schedule. For every finite τ with $d_P > 0$, $A(\tau) < A_{CM}$. If $A_{min} > A_{CM}$, fixed-age PM cannot meet that requirement in this model. Under exponential lifetimes and positive planned intervention costs, fixed-age replacement increases expected cost per operating-day relative to corrective restoration alone. Memorylessness means that replacing a surviving component does not reduce its subsequent hazard. Inspection, hazard-removing repair, battery ageing interventions and safety maintenance may nevertheless provide benefits when their effects are supported by an appropriate model and field evidence.

For grouped maintenance, system cost is assembled over actual visits and system outage intervals. Shared travel can reduce mobilization expenditure relative to separate visits, and simultaneous work may reduce total service downtime, but component downtime cannot simply be summed when outages overlap. Common-cause failures, shared crews, and spares require a system event or simulation model. Condition-triggered maintenance additionally requires monitoring costs, detection lead times, false-alarm and missed-failure probabilities, and the effect of action on the lifetime or restoration process. Cleaning is evaluated separately through recovered energy or service value against cleaning and travel costs, without treating soiling removal as renewal of hardware failure age. Calibration requires verified component inventories and event eligibility, operating ages and censoring, intervention types and effectiveness, parts and labour costs, trip distances and charges, planned outage durations, corrective response and spare-parts delays, monitoring costs, required service windows and valuation of unmet load. Battery chemistry, cycling, retained-capacity criteria and manufacturer limits are also needed. These quantities were unavailable in the aggregate dataset. Therefore, the present comparison is analytical and conditional; it does not yield local cost savings, measured availability, or a numerical optimal interval.

4. Results and discussion

4.1. Results

4.1.1. Respondent survey findings

The analysis included 280 complete and usable responses, exceeding the conditional minimum sample size of 241. The number of eligible users approached, and the numbers of non-responding or excluded users were not independently documented, so no response rate is reported. A complete-case analysis was applied without statistical imputation. Survey percentages in Figs. 4–9 use $n = 280$ as the denominator. Figs. 4–6 describe reported downtime, component problems, and maintenance frequency in Lango, Uganda.

Fig. 4 summarises reported restoration durations for the 280 systems. Seventy respondents (25.0%) reported restoration within one day, 130 (46.4%) reported 2–3 days, 60 (21.4%) reported 4–7 days, and 20 (7.1%) reported more than one week. The 2–3-day category was the most frequent, but did not constitute a majority on its own. Combining the first two categories, 200 respondents (71.4%) reported restoration within three days. These are respondent-level duration categories, not a dated register of every outage. They do not establish mean repair time, recurrence intervals, cumulative downtime or the fraction of observation time that systems were operational. Possible contributions from technician access, diagnosis, spare parts and financing require event-level investigation [38].

Fig. 5 presents respondents' reported frequency categories for component problems. About 70% placed batteries in the frequent or very frequent categories, compared with about 43% for inverters. About 61% placed solar-panel problems in the occasional or frequent categories. These response proportions describe recalled experience. They do not identify dated functional failures or provide the event counts used in Table 5. The survey highlights perceived component problems independently of the aggregate event-rate analysis. Related studies provide technical context [39–41].

Fig. 6 shows reported maintenance frequency by component. Monthly-to-quarterly servicing was reported for batteries by 78.6% of respondents; quarterly-to-semi-annual servicing was reported for inverters by 75%, and quarterly-to-semi-annual servicing for panels by 67.9%. Charge controllers, wiring, and mounting structures were generally serviced annually. These are descriptions of maintenance practice, not evidence of the frequency of functional failures or the effectiveness of servicing. Routine cleaning and preventive checks are distinct from corrective work after a qualifying failure. Maintenance approaches are discussed more broadly by Hernández-Callejo et al. [42].

Fig. 7 presents respondents' ratings of environmental influences on PV performance. Dust accumulation was frequently reported as a concern (65%). Respondents also reported effects associated with irradiance, rainfall, temperature, and shading. These ratings describe perceptions and do not establish causal effects, measured energy losses, or statistical differences between factors. In particular, a lower perceived impact does not demonstrate that a system is adapted to temperature or shading. The findings identify questions for field measurement; broader evidence on dust impacts is reviewed in [43].

Fig. 8 summarises respondents' ratings of technical influences. System design and installation were identified as concerns by 50% of respondents and regular maintenance by 32%. The corresponding reported proportions for component quality and system age were 9% and 5%. These descriptive responses do not establish independent associations with failure frequency or rank the causal importance of these factors. Testing such relationships requires respondent-level data and appropriate adjustment for operating conditions.

Fig. 9 summarises perceived socio-economic influences. Public awareness and training were rated as having a high impact by 40% of respondents, while availability of funds was rated as having a moderate impact by 50%. Technician availability was rated as having a slight impact by 50%, and government policy support as having a slight impact by 45%. These ratings identify perceived constraints; they do not demonstrate statistically significant effects on reliability. Table 3 presents the expert FMEA assessment, which is separate from these survey ratings.

4.1.2. Expert FMEA scores

Table 3 reports mode-specific RPN scores of 192 for panel soiling, 180 each for battery overheating and inverter conversion problems, and

128 for controller problems. The largest score therefore concerns a panel performance condition, whereas batteries and inverters have the largest aggregate reported-event rates in Table 5. These measures have different endpoints and do not establish a single ranking of intrinsic hardware reliability. Soiling prioritises inspection and cleaning but is not automatically a qualifying failure. Overheating, conversion and regulation problems qualify as functional failures only when they meet Section 3.5.2. The FMEA guides candidate actions; it does not validate event counts or demonstrate that those actions reduce failures.

4.1.3. Conditional mean time between failures calculations

Table 4 presents conditional MTBF derived solely from the aggregate counts and nominal exposure in Table 5 using Eq. (4). No respondent percentage enters this calculation. These durations represent MTBF only if the reported events satisfy the component functional-failure definition in Section 3.5.2; otherwise, they are mean nominal exposure per reported event. Annual survival probabilities are model outputs reported separately in Table 6.

The derived durations were 222.17 days for solar panels, 105.91 days for batteries, 148.12 days for inverters, and 329.68 days for charge controllers. Subsequent reliability calculations use the unrounded ratios from the aggregate event counts and nominal exposure. These durations remain conditional on the exposure denominator and event classification.

4.1.4. Aggregate event rates and conditional failure-rate estimates

Table 5 presents the count and nominal exposure inputs used to calculate $\widehat{\lambda_i} = \frac{N_i}{T_i}$, together with the resulting rate estimates and central two-sided 95% Poisson/chi-square confidence intervals. Rate estimation preceded calculation of MTBF and all subsequent reliability outputs. Confidence limits were calculated from N_i and T_i directly, rather than from rounded MTBF values.

Batteries had the highest estimated rate, 0.009442 day^{-1} (95% CI: 0.008856–0.010057), followed by inverters at 0.006751 day^{-1} (0.006257–0.007275), solar panels at 0.004501 day^{-1} (0.004099–0.004932) and charge controllers at 0.003033 day^{-1} (0.002705–0.003390). The sum of the unrounded component rates was 0.023728 day^{-1}; batteries and inverters contributed 68.25% of that series-model rate. These rates are conditional on the nominal denominator and the interpretation of the aggregate counts as eligible failures. Because the event categories cannot be separated, the numerical ordering describes the aggregate reported-event rates and does not establish an ordering of confirmed functional-failure rates. This numerical ordering is based only on the aggregate counts and nominal exposure; the percentages in Figs. 5–9 provide no evidence for it.

4.1.5. Conditional component reliability

The reliability function $R(t)$ is the probability of operation without a qualifying failure up to operating time t. Table 6 gives conditional component values at 180 and 365 days under the exponential model. These are fixed durations rather than exact six- and twelve-calendar-month observation windows.

At 180 and 365 days, respectively, calculated reliability was 44.5% and 19.3% for solar panels, 18.3% and 3.2% for batteries, 29.7% and 8.5% for inverters, and 57.9% and 33.1% for charge controllers. Charge controllers had the highest calculated reliability and batteries the lowest. These values remain conditional on the nominal exposure, constant hazard, and specified event counts.

4.2. Interpretation of model outputs and candidate maintenance actions

Fig. 10 presents expert FMEA scores alongside aggregate reported-event rates, derived conditional MTBF and modelled reliability. The panels retain the distinct endpoints and data sources used in the two analyses.

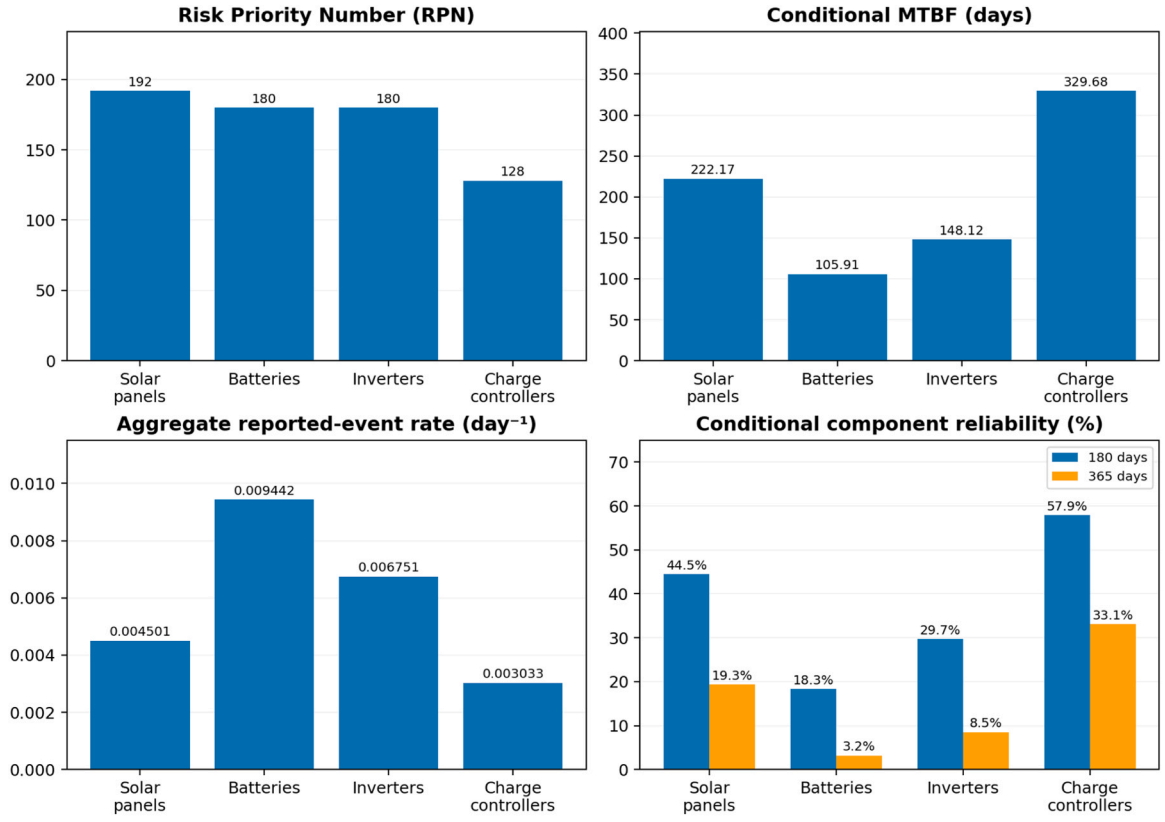

Fig. 10. Separate summaries of expert FMEA scores and aggregate-event model outputs. RPNs use expert scores; λ, conditional MTBF, and reliability use counts and nominal exposure. Survey percentages are not inputs to these panels.

Fig. 10 summarises the FMEA and derived reliability results. RPN values were 192 for solar panels, 180 for batteries, 180 for inverters and 128 for charge controllers. The corresponding MTBF values were 222.17, 105.91, 148.12, and 329.68 days. Component reliability at 180 days was 44.5%, 18.3%, 29.7% and 57.9%, respectively; at 365 days it was 19.3%, 3.2%, 8.5% and 33.1%. The rate-dependent values use unrounded N_i/T_i ratios and are conditional on the common nominal exposure.

4.2.1. Proposed maintenance framework

The proposed maintenance framework identifies inspection, servicing and corrective-restoration actions. Survey reports describe user concerns and practical service constraints, while expert FMEA scores identify mode-specific priorities. Aggregate event counts and exposure supply a separate, conditional rate model. Candidate action selection does not establish that respondent perceptions predict failure risk, and neither an implemented policy nor an empirically optimal schedule was demonstrated.

4.2.2. Candidate preventive maintenance actions

Table 7 identifies candidate maintenance actions and the evidence needed to initiate them. Inspection frequency, battery replacement and other planned interventions require manufacturer instructions, service requirements and condition evidence. The survival-quantile equation does not establish a beneficial intervention interval. Economic and availability comparisons use Section 3.8; no fixed replacement interval is selected from the present aggregate rates.

4.3. Discussion

Under the independent exponential series model, calculated uninterrupted system reliability was 1.40% at 180 days and 0.01733% at 365 days. Component MTBF values were 222.17 days for solar panels, 105.91 days for batteries, 148.12 days for inverters, and 329.68 days for charge controllers. The component confidence intervals describe Poisson sampling uncertainty conditional on the nominal exposure; they do not establish the accuracy of that exposure or provide simultaneous bounds for system reliability. The conditional series-model mean of 42.14 days and the restoration durations in Fig. 4 concern different quantities. The former is the modelled mean operating time to the first qualifying interruption; the latter describes respondents' reported time to restoration. A repairable system can experience interruptions and return to service after each one. Consequently, short restoration durations are conceptually compatible with relatively frequent failures, and low uninterrupted mission reliability does not by itself establish low service availability.

Under an alternating operating-and-restoration process, long-run availability depends on mean operating duration relative to mean operating duration plus mean total downtime, as represented in Eq. (13). This relationship cannot be evaluated by treating the modal 2–3-day category as a mean restoration time. The open-ended category above one week, the absence of system-outage recurrence counts, and the lack of linked observation and restoration histories prevent estimation of cumulative service time or numerical availability from Fig. 4. The figure therefore does not support a claim that most systems remained operational over the observation period. The present data also do not demonstrate that a typical system actually fails every six weeks. The series rate combines aggregate component reports whose failure classification, component inventory, independence, and at-risk exposure are unverified. Those reports cannot be linked to the respondent-level restoration categories on a common observation basis. Thus, the apparent gap is explained conceptually by the difference between failure occurrence and restoration, but cannot be reconciled empirically from the available summaries. Dated system-level failure and restoration records, linked to component events and operating exposure, are required to estimate both recurrent failure frequency and operational availability.

No preventive-replacement interval or PM-induced reliability improvement is established. Eq. (6) retains the same λ under every policy considered in the exponential comparison. Replacement of a surviving component therefore does not reduce its subsequent hazard, and a survival quantile is not evidence of a useful intervention age. Planned maintenance can interrupt service, which is represented separately by the availability model. Potential shared-travel or overlapping-outage savings concern logistics and service time, not an inferred improvement in hardware reliability. The aggregate-event calculations identify batteries and inverters as candidates for rate-focused investigation, subject to endpoint and exposure verification. Survey reports identify user concerns independently and do not validate rate-based ordering.

4.3.1. Benchmarking against published field reliability evidence

The aggregate rates were expressed on a common nominal annual basis using $\lambda_{i,year} = 365\lambda_{i,day}$, without changing the event definition. The resulting frequencies were 1.6429 events per nominal component-year for solar panels, 3.4464 for batteries, 2.4643 for inverters, and 1.1071 for charge controllers. Their reciprocals were 222.17, 105.91, 148.12 and 329.68 days, respectively. These are exposure-per-event quantities; they represent hardware MTBF only when the events meet the functional-failure definition. Table 8 compares them with published field measurements while retaining each source's unit, endpoint, and observation basis. IEA-PVPS Task 13 distinguishes power degradation, defects, safety failures, and recoverable soiling losses, and its field-failure survey records system configuration, dates, failure mode, and power impact [44]. These distinctions preclude treating every performance problem as a failed module. The Task 13 report supports endpoint-specific assessment rather than a universal module hazard or MTBF applicable to all technologies and climates. In particular,

Table 7
Candidate component maintenance actions and decision criteria.

Component	Candidate action	Initiation and decision evidence	Service constraint	Maintenance tasks
Panels	Inspection and cleaning	Measured soiling or output loss; visible damage; manufacturer inspection requirements.	Separate recoverable soiling losses from hardware failure.	Clean panels to remove dust and soiling; inspect for cracks and physical damage; check electrical connections and output performance.
Batteries	Condition assessment; justified replacement	Chemistry-specific voltage, temperature, cycle history and retained-capacity tests; manufacturer limits.	Required storage autonomy and critical-load service, assessed separately from state of charge and retained capacity.	Check voltage and temperature; inspect electrolyte levels where applicable; assess charge–discharge cycles; inspect for corrosion, leakage and terminal damage.
Inverters	Inspection, diagnosis and restoration	Diagnostic alarms, thermal or ventilation condition, electrical tests and manufacturer instructions.	Verify safe operation and required load supply.	Clean ventilation systems and heat sinks; inspect electrical connections; check for overheating and component degradation; perform firmware updates where applicable.
Controllers	Inspection, testing and restoration	Charging regulation, temperature, connection integrity, and protection tests.	Maintain battery protection and safe charging limits.	Inspect voltage and current regulation; perform thermal checks; verify component and connection integrity; conduct functional testing.

Table 8
Comparison of aggregate event rates with published field reliability evidence.

Component	Present aggregate calculation	Published field evidence	Comparability and interpretation
Solar panels	$\lambda = 0.004501$ day^{-1}; 1.6429 events/year. Reciprocal = 222.17 days (0.609 years).	NREL-led field study: annualized module-issue occurrence 0.02–0.19% by system-size group [45]. Task 13 separates module failures, degradation and soiling [44].	System-report occurrence is not a per-module hazard. The 222-day value is not established as intrinsic module lifetime.
Inverters	$\lambda = 0.006751$ day^{-1}; 2.4643 events/year. Reciprocal = 148.12 days (0.406 years).	NREL-led field study: annualized inverter-issue occurrence 0.76–6.95% by system-size group [45].	Whole-system reports and individual inverter events have different denominators; no device MTBF is inferred from these percentages.
Batteries	$\lambda = 0.009442$ day^{-1}; 3.4464 events/year. Reciprocal = 105.91 days (0.290 years).	Moroccan SHS field study: fitted MTTF ≈5.5 years with an age-dependent failure distribution [46].	Field battery replacement life is approximately 19 times the present reciprocal; capacity-based endpoints can be much earlier [47]. No constant reference λ is assumed.
Charge controllers	$\lambda = 0.003033$ day^{-1}; 1.1071 events/year. Reciprocal = 329.68 days (0.903 years).	Moroccan SHS field study: constant λ = 0.0367 year^{-1} = 0.00010055 day^{-1}; MTTF ≈27.2 years [46].	The present aggregate rate is approximately 30 times the reference rate; classification and exposure differences remain unresolved.
Four-block series model	$\Sigma\lambda = 0.02372798$ day^{-1} = 8.6607 events/year. Model mean to first event = 42.14 days.	No matched field system benchmark is available for the same four-block configuration and endpoint.	The 42-day result is a model implication, not an observed system MTBF or whole-system replacement lifetime.

percentage power loss per year is not a probability or frequency of hardware failure and cannot be inverted to obtain MTBF.

Jordan et al. analysed approximately 100,000 US PV systems using annual reports extending to five years [45]. Their annualized module- and inverter-issue occurrences (Table 8) are much lower than the present frequencies, but are system-report measures rather than individual-device hazards. A system may contain multiple components; the published percentages are therefore not inverted to obtain device MTBF. No matched failure-rate ratio is inferred from this comparison. For off-grid storage and control equipment, Carrasco et al. analysed five years of Moroccan solar-home-system maintenance data, retaining 7595 systems after data cleaning [46]. Their fitted battery MTTF was approximately 5.5 years with an age-dependent distribution, whereas the present exposure-per-event value is 0.290 years. The controller fit used a constant rate of 0.0367 year^{-1}, equivalent to 0.00010055 day^{-1} and an exponential MTTF of approximately 27.2 years, compared with 1.1071 events/year and 0.903 years here. The controller rate is therefore about 30 times the reference rate on the stated exposure basis. These are comparisons between different populations and event definitions, not estimates of a causal regional effect. The battery MTTF is not inverted to impose a constant battery hazard.

Endpoint choice is particularly important for batteries. In field testing of lead-acid batteries from the same Moroccan programme, remaining capacity crossed 80% within six months even though the replacement-based failure database described much longer service [47]. Capacity-threshold life and replacement-based MTTF therefore describe different endpoints. This evidence does not validate the present 105.91-day value as a replacement lifetime. Battery chemistry, capacity, cycling, operating conditions, and the failure threshold are insufficiently specified in the Lango aggregate summaries for a matched comparison. Sandia's PVROM analysis of more than 800 US systems likewise derives field-failure distributions from identified events and exposure histories [48]. It separates component failure patterns from environmental conditions and supports non-constant failure distributions where appropriate. The benchmark data were used to assess plausibility, rather than substituted for the Lango counts or used to calibrate them.

Annualization uses 365 days/year and the unrounded rates in Table 5. The NREL percentages are annualized issue occurrences per reporting system, not component hazard probabilities; no reference MTBF is calculated from them. MTTF denotes mean time to first failure under each source's fitted lifetime distribution. The listed studies are external benchmarks and do not replace or independently validate the Lango records. For the independent exponential four-block model, the combined rate is 0.02372798 day^{-1} and the mean operating time to the first model event is 42.14 days. This is not an observed system MTBF, a component replacement lifetime, or an observed calendar recurrence interval. Interpreting it as a recurrent mean operating time would require a validated failure process and documented restoration assumptions. System outage times, repair cycles, component multiplicity, and coincident events were unavailable. Component reports also cannot be summed as independent system outages when they describe one common incident or include soiling and routine maintenance. The 42-day value is therefore a conditional implication of the aggregate inputs and series assumptions; it does not establish physical failure or replacement of a typical PV system every six weeks.

The benchmark discrepancies are not evidence that the Lango hardware has exceptionally short intrinsic lifetimes. Differences in technology, loading, installation quality and environment could affect reliability, but their contributions cannot be quantified from these summaries. Event misclassification, repeated reports, inconsistent module-versus-assembly counting and an incorrect exposure denominator are also plausible explanations that require verification. Consequently, the 222-day panel value and 42-day series value are retained only as conditional arithmetic diagnostics. Neither is used as an established hardware lifetime or evidence for an optimized replacement schedule. The external evidence supports validation and reclassification of the original events before quantitative field-failure conclusions are drawn. Electrical function tests combined with EL or IR inspection offer a prospective basis for classifying suspected panel events [23,24,29]. Component identifiers, inspection dates, defect types, measured electrical effects, operating exposure and restoration histories provide the linkage between a diagnostic observation and a qualifying failure episode. This linkage distinguishes cracks, thermal anomalies and degradation indicators from confirmed loss of the required function. Such records would complement the published field benchmarks and permit verification of the aggregate event classifications.

4.3.2. *Analytical cost and availability policy comparison*

Table 9 compares four maintenance policy classes using the explicit cost and availability definitions. The exponential baseline yields an analytical result without assigning unobserved prices or restoration times: fixed-age replacement does not improve availability when it adds service downtime, and its calendar-cost objective has no strict interior minimum. A survival quantile therefore does not identify an economic optimum. The sign of the cost comparison and the feasibility of the service requirement cannot be evaluated numerically from the aggregate counts. These are cost and availability comparisons under an unchanged exponential hazard, not estimates of a PM effect on $R(t)$. A claim of improved reliability would require a validated relation between a specified intervention and the subsequent failure process, which the

Table 9
Analytical comparison of maintenance policies.

Policy	Cost and availability basis	Analytical implication	Evidence needed for selection
Corrective restoration	$G_{CM} = \frac{Q_C}{B}$ $A_{CM} = \frac{1}{1+\lambda d_C}$	Reference case for a single non-redundant block; admissible only when safety and service requirements permit.	Corrective costs, complete restoration durations and required availability.
Fixed-age replacement plus CM	$G(\tau)$, $A(\tau)$ in (13–15).	With exponential lifetimes, no hazard reduction; positive planned downtime lowers availability. Cost is monotone or constant in z.	Age-dependent lifetime evidence, restorative effect, PM/CM costs and downtime.
Grouped planned visits plus CM	General $J(\pi)$, $A(\pi)$, with one travel charge per shared visit and union of system outages.	Potential travel and outage savings relative to separate visits; no assumed reduction in hardware hazard.	Visit routes, shared work scope, crew capacity, costs and outage overlap.
Condition-triggered action plus CM	General $J(\pi)$, $A(\pi)$, including monitoring and false-alarm interventions.	Benefit depends on detection and an effective action; no calibrated ranking available.	Monitoring costs, alarm performance, lead time and demonstrated intervention effect.

available data do not support.

4.4. Study limitations

The analysed sample of 280 exceeded the conditional planning minimum of 241, but this numerical excess does not establish survey precision or representativeness. The household base and assumed adoption shares of 20 and 10% were unverified, while $p = 0.80$ was not an observed outcome proportion among eligible PV owners. The household scenario also omitted separate enumeration of institutions and businesses. Stratum populations, allocation totals, selection probabilities and a verified recruitment denominator were unavailable. Response rate, proportional allocation and geographic coverage therefore remain unverified. Individual sampled-site locations and district-specific response counts were unavailable, so Fig. 3 provides an administrative locator rather than a map of the realised sample.

The aggregate expressions establish event counts and nominal exposure factors, but do not provide an independently auditable event register. Observation dates, system and component identifiers, component multiplicity, recurrent-event histories, downtime exclusions and censoring adjustments were unavailable. The nominal denominator cannot be verified as net at-risk operating exposure. An inconsistent separate inverter summary has an unspecified observation basis and was excluded from the rate calculations. MTBF was derived from the estimated rate and supplies no independent validation. The Poisson confidence intervals quantify count uncertainty conditional on the denominator and model; they do not capture exposure error, clustering or event misclassification. The reported events cannot be separated retrospectively into functional failures, soiling, minor faults and maintenance actions, and the component unit cannot be verified as module, battery, bank or functional assembly. The rates and dependent reliability outputs therefore remain conditional calculations rather than confirmed hardware-failure estimates. The discrepancies from published field evidence in Section 4.3.1 cannot be attributed to regional operating conditions without matched endpoints and event histories. The 222-day panel reciprocal and 42-day series-model mean are not validated replacement lifetimes or observed system recurrence intervals.

The model assumes constant rates, memoryless lifetimes, independent component failures and a non-redundant series configuration. Early-life failures, ageing, degradation, common environmental or electrical stresses, and installed redundancy can violate these assumptions. The available aggregates cannot identify the appropriate time-dependent or dependent-failure model. The calculated survival values are consequently conditional projections for the stated baseline configuration. Under the constant-rate assumption, replacement of a functioning component with an identical component does not reduce its subsequent failure hazard. Scheduled visits provide a possible framework for manufacturer-required inspections, safety checks, condition assessment, cleaning of observed soiling, and coordination of personnel and spare parts. Their timing depends on those requirements and observed conditions. Potential benefits, including recovered output, removal of documented hazards or shorter restoration delays, concern mechanisms outside the present constant-hazard equation and were not measured. Planned visits also incur costs and may interrupt service. A net availability or economic benefit therefore remains unestablished, and the analysis provides no validated preventive interval.

Grouped restoration reports do not distinguish active repair from technician response, spare-parts waiting or administrative delay. Component MTTR, repair rates, maintainability functions and empirical availability were therefore not estimated. The reports cannot be linked to aggregate component events over a common observation window and cannot validate the conditional 42-day model result. The cost and availability formulation likewise remains uncalibrated because policy-specific costs, outage durations, and intervention effects were unavailable. Its analytical comparisons do not establish a numerical cost-minimizing policy or a local service-availability result. The survey analysis was descriptive. Respondent-level observations were unavailable for hypothesis testing, effect-size estimation, or multivariable adjustment. The percentages describe reported experiences and perceived influences; they do not establish statistically significant, independent, or causal associations with failure frequency or downtime. Recall bias and unmeasured operating conditions further limit their interpretation.

5. Conclusion

The survey identifies reported maintenance problems and service constraints in rural PV systems in Lango. Batteries and inverters had the highest aggregate reported-event rates under the nominal exposure, making them candidates for closer investigation; this ordering was not inferred from respondent percentages and does not establish intrinsic hardware reliability. The FMEA separately prioritised panel soiling, a performance condition that must be distinguished from hardware failure. Rate estimates and their Poisson confidence intervals remain conditional on event eligibility and nominal exposure. The 222-day panel reciprocal and 42-day model mean to first event are not validated hardware lifetimes or observed system recurrence intervals. Reported restoration durations describe a different endpoint and do not establish that most systems remained operational or quantify service availability. The constant-hazard reliability model contains no maintenance-effect term and predicts no PM-induced reliability gain at equal operating exposure. The cost and availability model compares intervention expenditure and service downtime under that unchanged hazard; it does not establish a numerical optimal schedule or justify fixed survival targets. No maintenance intervention was implemented or tested, so reduced downtime, cost savings and improved availability were not demonstrated. Socio-economic findings are descriptive perceptions rather than statistically significant or causal effects. Verified event histories, operating exposure, restoration durations and intervention costs are needed before applying the quantitative results to maintenance decisions.

5.1. Recommendations

The findings support three priorities for maintenance planning and subsequent evaluation.

1. **Maintenance policy evaluation:** The cost and availability formulation provides a basis for comparing corrective restoration, justified age replacement, and grouped visits. Numerical comparison depends on parts and labour costs, travel expenditure, required service windows, planned outages, failure-to-restoration histories, and unmet-load consequences. Service requirements reflect the needs of system owners and critical-load users; intervention effects remain empirical quantities rather than consequences of an assigned survival percentage.
2. Training and capacity building. Safe inspection, diagnosis, routine care, and timely fault reporting are relevant to the maintenance problems described by respondents. The effectiveness of training is an evaluation question concerning observed practice, restoration times, and delivered service. The present survey does not quantify a training-induced change in reliability.
3. Environmental and installation measures. Candidate measures include cleaning in response to measured soiling or recoverable output loss, and inspection of installation quality and electrical protection against manufacturer requirements. Their practical value depends on safe operation, delivered service, labour, water, travel and intervention expenditure. These outcomes were not evaluated as intervention effects in the present study.

6. Future work

Longitudinal component failure, restoration and censoring histories, validated exposure, and policy-specific costs and downtime provide the basis for testing maintenance effects. Age-dependent and common-cause models are prospective extensions to the constant-hazard series baseline. Evaluation of training, financing and repair access also requires measured restoration and service outcomes.

6.1. Feasibility of digital monitoring and remaining useful life prediction

Internet of Things (IoT) monitoring and remaining useful life (RUL) prediction are potential research extensions, not outputs of the present study. No sensors were deployed, no prediction model was trained or validated, and no technical or economic feasibility assessment was conducted for rural Lango. Their suitability therefore remains undetermined. A prospective feasibility assessment would compare manual inspection and local data logging with remote monitoring. Relevant site characteristics include communications coverage and outages, auxiliary power demand, sensor accuracy and durability, data completeness, technician skills, spare-part access and responsibility for responding to alarms. Local logging with delayed transmission is an option where continuous communications are unavailable. Candidate measurements include battery voltage, current, temperature and chemistry-specific capacity indicators, alongside inverter load, temperature and fault codes. Their value depends on a defined failure mechanism and an actionable intervention. Evaluation of an imaging or connected-monitoring pilot would include diagnostic accuracy against independently confirmed defects [24], device resource use and the communication overhead of security controls [27]. Acquisition, training, connectivity and security-maintenance expenditure belong within the Section 3.8 cost framework. No deployment benefit was measured in the present study.

The economic evaluation would include sensor and gateway acquisition and installation, calibration and replacement, power consumption, communications, software, storage, staffing, training, maintenance, cybersecurity support and false-alarm visits. Comparison over a common horizon would relate these costs to measured changes in corrective expenditure, travel, planned and unplanned downtime, and unmet-load value. The formulation counts shared trips and overlapping outages once. Affordability depends on user budgets and willingness to pay; savings and availability gains remain outcomes for evaluation. RUL modelling requires a defined functional-failure or capacity endpoint, component age, operating and intervention histories, and longitudinal run-to-failure and censored observations. Prospective or held-out-system evaluation against age- and condition-based baselines would quantify prediction uncertainty, calibration, error, detection lead time, false alarms and missed failures. Condition alerts may be more suitable than RUL estimates when failure histories are insufficient. Adoption depends on whether alerts lead to feasible interventions and improve cost and service outcomes relative to simpler alternatives.

List of acronyms

The following abbreviations are used in this manuscript:
AC Alternating Current
CM Corrective Maintenance
D Detection (in FMEA)
DC Direct Current
FMEA Failure Mode and Effects Analysis
IoT Internet of Things
KPIs Key Performance Indicators
kWKilowatt
kWh Kilowatt Hour
MTBF Mean Time Between Failures
O Occurrence (in FMEA)
PdM Predictive Maintenance
PM Preventive Maintenance
PV Photovoltaic
$R(t)$Reliability Function
RCM Reliability-Centered Maintenance
RPN Risk Priority Number
RUL Remaining Useful Life
S Severity (in FMEA)
SHS Solar Home System
SOC
UGX
λState of Charge
Ugandan Shilling
Failure Rate (Lambda)

Ethical declaration

This study involved human participants through surveys and interviews. Ethical approval was obtained from the Kampala International University Research Ethics Committee (REC), reference KIU-8282, before data collection commenced. Written or verbal informed consent was obtained from all participants, and confidentiality and data protection procedures were applied as described in Section 3.5.1.

Author contributions

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Declaration of Competing Interest

The author(s) declare no competing interests

Data availability statement

Aggregate survey summaries are presented in Figs. 4–9, final FMEA scores in Table 3, and aggregate component event counts, nominal exposures, and conditional rate estimates in Table 5. The rates were calculated directly from source-summary counts and exposure factors; MTBF was derived subsequently, and manufacturer failure rates or MTBF specifications were not numerical inputs. Individual participant records, individual expert scoring sheets and an anonymised failure-and-restoration register are not provided with the manuscript. Actual observation dates, component inventories, downtime adjustments, censoring histories and separate counts of functional failures, soiling, minor faults and maintenance events are unavailable for verification. Consequently, the published summaries reproduce the conditional calculations but do not permit independent event-level validation or respondent-level inference. Participant identities are not included in the reported aggregate material. No raw-data repository accession or supplementary event dataset is provided.

References

[1] E. Kabasingwa, "Assessing the Diffusion of Renewable Energy Technologies and Socio-economic Development: A Ripple Effect Analysis of Two Policy Choices: Inclusive Clean-burning, Fuel-efficient Cook-stoves and Solar PVs for Street Lighting, Institutional and Home Applications in Hoima District, Uganda," PAUWES, 2019.

[2] I. Kimuli, J.B. Kirabira, Research perspectives for improving regulation and policy development for energy efficiency and sustainable mobility in Uganda, iScience 28 (2025).

[3] O. Fred, K.J. Ukagwu, A. Abdulkarim, V.H.U. Eze, Reliability and maintainability analysis of solar photovoltaic systems in rural regions: a narrative review of challenges, strategies, and policy implications for sustainable electrification, KIU J. Sci. Eng. Technol. 3 (2024) 103–122.

[4] A.C. Groenewoudt, H.A. Romijn, F. Alkemade, From fake solar to full service: an empirical analysis of the solar home systems market in Uganda, Energy Sustain. Dev. 58 (2020) 100–111.

[5] A. Tillmans, P. Schweizer-Ries, Knowledge communication regarding solar home systems in Uganda: the consumers' perspective, Energy Sustain. Dev. 15 (2011) 337–346.

[6] S.O. Obatola, Reliability overview of grid-connected solar PV system: a review, Arch. Adv. Eng. Sci. (2024) 1–10.

[7] E.H. Sepulveda-Oviedo, Impact of environmental factors on photovoltaic system performance degradation, Energy Strategy Rev. 59 (2025) 101682.

[8] K. Hasan, S.B. Yousuf, M.S.H.K. Tushar, B.K. Das, P. Das, M.S. Islam, Effects of different environmental and operational factors on the PV performance: a comprehensive review, Energy Sci. & Eng. 10 (2022) 656–675.

[9] W. Ahmed, Y.W. Wu, A survey on reliability in distributed systems, J. Comput. Syst. Sci. 79 (2013) 1243–1255.

[10] I.P. Okokpujie, L.K. Tartibu, B.H. Omietimi, Improving the maintainability and reliability in Nigerian Industry 4.0: its challenges and the way forward from the manufacturing sector, Int. J. Sustain. Dev. & Plan. 18 (2023).

[11] J. Knezevic, Maintainability and system effectiveness. Handbook of Maintenance Management and Engineering, ed, Springer, 2009, pp. 547–610.

[12] M. Osman, I. Qureshi, Review of photovoltaic and concentrated solar technologies including their performance, reliability, efficiency and storage, Results Eng. (2025) 104424.

[13] E. Heylen, G. Deconinck, D. Van Hertem, Review and classification of reliability indicators for power systems with a high share of renewable energy sources, Renew. Sustain. Energy Rev. 97 (2018) 554–568.

[14] A.S. Maihulla, I. Yusuf, Reliability, availability, maintainability, and dependability analysis of photovoltaic systems, Life Cycle Reliab. Saf. Eng. 11 (2022) 19–26.

[15] R. Torres Navarro, C. Segura Quirós, L.D. Murillo Soto, C. Meza, Reliability, availability and maintainability analysis for grid-connected solar photovoltaic systems, 27533735251347993, Renew. Energ. 3 (2025), 27533735251347993.

[16] H. Abunima, J. Teh, Reliability modeling of PV systems based on time-varying failure rates, IEEE Access. 8 (2020) 14367–14376.

[17] Y.T. Wassie, M.S. Adaramola, Socio-economic and environmental impacts of rural electrification with Solar Photovoltaic systems: Evidence from southern Ethiopia, Energy Sustain. Dev. 60 (2021) 52–66.

[18] G. Alinaitwe, Bringing power to the people of Uganda: determinants of solar photovoltaics adoption in Uganda, J. Serv. Sci. Manag. 16 (2023) 391–408.

[19] R.J. Mustafa, M.R. Gomaa, M. Al-Dhaifallah, H. Rezk, Environmental impacts on the performance of solar photovoltaic systems, Sustainability 12 (2020) 608.

[20] B. Aboagye, S. Gyamfi, E.A. Ofosu, S. Djordjevic, Investigation into the impacts of design, installation, operation and maintenance issues on performance and degradation of installed solar photovoltaic (PV) systems, Energy Sustain. Dev. 66 (2022) 165–176.

[21] K. Osmani, A. Haddad, T. Lemenand, B. Castanier, M. Ramadan, A review on maintenance strategies for PV systems, Sci. Total. Environ. 746 (2020) 141753.

[22] R. Pimpalkar, A. Sahu, R.B. Patil, A. Roy, A comprehensive review on failure modes and effect analysis of solar photovoltaic system, Mater. Today. Proc. 77 (2023) 687–691.

[23] S. Verma, D.K. Yadav, B. Bora, S. Lal, Quantifying mechanical stress effects on mono PERC and polycrystalline PV modules with EL imaging and statistical analysis (art.), Unconv. Resour. 9 (2026) 100276, https://doi.org/10.1016/j.uncres.2025.100276.

[24] S. Verma, S. Lal, A. Joshi, and H. Ul Hasan Khan, "Defect detection in solar photovoltaic modules using IR imaging and YOLOv11," in Proc. 2026 IEEE Madhya Pradesh Section Conference (MPCON), Gwalior, India, 2026, pp. 1362–1366, doi:10.1109/MPCON69668.2026.11508398.

[25] S. Hussain, R.K. Prajapati, M. Kumar, V. Kumar, S.K. Sharma, S.L. Meena, S. Lal, S. Verma, Sustainable solar energy policies: Significance and impact for sustainable development, Int. J. Environ. Sci. 11 (20s) (Aug. 2025) 1535–1546, https://doi.org/10.64252/8eegd302.

[26] S. Lal, S. Choudhary, S. Verma, V.K. Jaiswal, S.V. Desale, A. Shrivastava, Application of artificial intelligence approach for carbon reduction through RES in buildings, Int. J. Environ. Sci. 11 (7s) (Jun. 2025) 1088–1103, https://doi.org/10.64252/c1nkyn18.

[27] B.S. Chauhan, S. Verma, S.K. Sharma, and S. Lal, "Performance assessment of lightweight end-to-end encryption protocols for solar PV IoT devices," in Proc. 2026 IEEE Madhya Pradesh Section Conference (MPCON), Gwalior, India, 2026, pp. 689–693, doi:10.1109/MPCON69668.2026.11508461.

[28] S. Choudhary, S. Lal, S. Verma, Seasonal optimization of solar PV tilt angles for enhanced energy efficiency in Rajasthan, India (art.), Unconv. Resour. 8 (2025) 100230, https://doi.org/10.1016/j.uncres.2025.100230.

[29] S. Verma, D.K. Yadav, Recent research and developments of degradation assessment and its diagnosis methods for solar PV plant: A review, Int. J. Appl. Power Eng. 13 (2) (Jun. 2024) 483–498, https://doi.org/10.11591/ijape.v13.i2.pp483-498.

[30] J. Carretero, J.M. Pérez, F. García-Carballeira, A. Calderón, J. Fernández, J. D. García, et al., Applying RCM in large scale systems: a case study with railway networks, Reliab. Eng. & Syst. Saf. 82 (2003) 257–273.

[31] A.U. Adoghe, Reliability centered maintenance (RCM) for asset management in electric power distribution system, Covenant University, 2010.

[32] Uganda Bureau of Statistics, with support from WHO, Uganda district administrative boundaries, layer uga_admbnda_adm2_ubos_20200824_epsg3857, 24 August 2020, hosted by UNITAR–UNOSAT. https://unosat-geodrr.cern.ch/data/rest/services/Hosted/UGA_District_Boundary/FeatureServer/23 (accessed 25 October 2026).

[33] K.D. Sharma, S. Srivastava, Failure mode and effect analysis (FMEA) implementation: a literature review, J. Adv. Res. Aeronaut. Space Sci. 5 (2018) 1–17.

[34] J. Huang, J.-X. You, H.-C. Liu, M.-S. Song, Failure mode and effect analysis improvement: A systematic literature review and future research agenda, Reliab. Eng. & Syst. Saf. 199 (2020) 106885.

[35] NIST/SEMATECH, e-Handbook of Statistical Methods, Section 8.4.5.1, Constant repair rate (HPP/exponential) model." https://www.itl.nist.gov/div898/handbook/apr/section4/apr451.htm (accessed 25 October 2026).

[36] R. Barlow, L. Hunter, Optimum preventive maintenance policies, Oper. Res. 8 (1) (1960) 90–100, https://doi.org/10.1287/opre.8.1.90.
[37] NREL, Sandia National Laboratories, SunSpec Alliance, and the SunShot National Laboratory Multiyear Partnership (SuNLaMP) PV O&M Best Practices Working Group, Best Practices for Operation and Maintenance of Photovoltaic and Energy Storage Systems, 3rd ed., Report NREL/TP-7A40-73822, December 2018. https://www.nrel.gov/docs/fy19osti/73822.pdf.
[38] A. Abubakar, C.F.M. Almeida, M. Gemignani, A review of solar photovoltaic system maintenance strategies, 2021 14th IEEE Int. Conf. Ind. Appl. (INDUSCON) (2021) 1400–1407.
[39] S. Sulaeman, M. Benidris, J. Mitra, Modeling and assessment of PV solar plants for composite system reliability considering radiation variability and component availability, 2016 Power Syst. Comput. Conf. (PSCC) (2016) 1–8.
[40] O. Kim, N. Matchanov, M. Malikov, B. Umarov, A study of main causes of malfunction and breakdown for PV inverter and suggestion of some practical measures, Appl. Sol. Energy 53 (2017) 35–38.
[41] V. Sharma, S.S. Chandel, Performance and degradation analysis for long-term reliability of solar photovoltaic systems: A review, Renew. Sustain. Energy Rev. 27 (2013) 753–767.
[42] L. Hernández-Callejo, S. Gallardo-Saavedra, V. Alonso-Gómez, A review of photovoltaic systems: Design, operation and maintenance, Sol. Energy 188 (2019) 426–440.
[43] A. Eleftheriou, P. Mouzourides, G. Biskos, P. Yiallouros, P. Kumar, M.K.-A. Neophytou, The challenge of adopting mitigation and adaptation measures for the impacts of sand and dust storms in the Eastern Mediterranean Region: a critical review, Mitig. Adapt. Strateg. Glob. Change 28 (2023) 33.
[44] M. Köntges et al., Assessment of Photovoltaic Module Failures in the Field, IEA-PVPS Task 13, Report T13-09:2017, May 2017. https://iea-pvps.org/wp-content/uploads/2017/09/170515_IEA-PVPS-report_T13-09-2017_Internetversion_2.pdf.
[45] D.C. Jordan, B. Marion, C. Deline, T. Barnes, M. Bolinger, PV field reliability status: Analysis of 100,000 solar systems, Progress. Photovolt. Res. Appl. 28 (8) (2020) 739–754, https://doi.org/10.1002/pip.3262.
[46] L.M. Carrasco, L. Narvarte, A. Peral, M. Vázquez, Reliability of a 13,000-SHS photovoltaic rural electrification programme, Progress. Photovolt. Res. Appl. 21 (5) (2013) 1136–1145, https://doi.org/10.1002/pip.2218.
[47] L.M. Carrasco, L. Narvarte, F. Martínez-Moreno, R. Moretón, In-field assessment of batteries and PV modules in a large photovoltaic rural electrification programme, Energy 75 (2014) 281–288, https://doi.org/10.1016/j.energy.2014.07.074.
[48] T. Gunda and R. Homan, Evaluation of Component Reliability in Photovoltaic Systems Using Field Failure Statistics, Sandia National Laboratories, Report SAND2020-9231, September 2020. https://doi.org/10.2172/1660804.